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Unemployment Dynamics and Duration Dependence

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A major issue in the analysis of unemployment durations concerns distinguishing genuine duration dependence of the exit rate out of unemployment from unobserved heterogeneity. We present a method for the nonparametric estimation of both phenomena, designed to be applicable to time-series data on aggregate outflows from different duration classes. The model explicitly takes into account that individual exit rates are affected by the business cycle and by seasonal effects. The method is applied to U.S. data. We find diverging duration effects among black and white individuals. However, except for white males, duration dependence is dominated by unobserved heterogeneity.

I. Introduction

In the past decade, the econometric analysis of unemployment durations has become widespread. One of the major issues in this literature concerns the distinction between duration dependence of the hazard rate (or exit rate out of unemployment) and unobserved heterogeneity (for surveys, see, e.g., Lancaster 1990; and Devine and Kiefer 1991). Often, there is reason to believe that for a given individual the hazard rate decreases as a function of duration. For example, there may be stigma effects reducing the number of job opportunities for the long-term unemployed (see, e.g., Vishwanath 1989; and Van den Berg 1994).

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However, the presence of unobserved heterogeneity in the distribution of the duration variable causes the hazard rate of the distribution of observed durations to decrease as well. This follows from the fact that, on average, individuals with the largest hazard rate leave unemployment first. Obviously, from a policy point of view, it is important to know the relative importance of genuine duration dependence (also called state dependence) on the one hand and unobserved heterogeneity on the other. For example, if duration dependence is the dominant factor, then efforts may be concentrated on the long-term unemployed, while otherwise it may be useful to screen short-term unemployed and concentrate efforts on those with bad characteristics. However, since both factors affect the hazard rate in a similar way, it seems to be hard to distinguish empirically between them.

It is known that in the class of mixed proportional hazard (MPH) models, both the shape of the duration dependence of the hazard and the distribution of the unobserved heterogeneity are nonparametrically identified (see Elbers and Ridder 1982). However, it is generally believed that in practice it is next to impossible to distinguish between these elements if no strong prior information is present on the shape of the duration dependence or the heterogeneity distribution. In any case, up to now no nonparametric estimation strategy has been developed.

Therefore, in reduced-form empirical analysis of unemployment durations, it has been common to make functional form assumptions on (i) the shape of the duration dependence, (ii) the distribution of unobserved heterogeneity, and (iii) the way the observed explanatory variables enter the model. For example, typical choices are (i) Weibull duration dependence, (ii) gamma-distributed unobserved heterogeneity, and (iii) log-linear dependence of the hazard on observed explanatory variables (see the surveys mentioned above and the references therein). Sometimes more flexible forms are chosen, or semiparametric approaches are followed in which only part of the assumptions mentioned above are made. In any case, the results are conditional on the particular parametric parts of the specification. Intuitively, it is clear that the results on the degree of duration dependence and unobserved heterogeneity may be extremely sensitive with respect to misspecification of the corresponding parts of the model. As an example, Ridder (1987) proves that estimates may be heavily biased if the form of the duration dependence is misspecified. Since in general the choice of this specification is based on analytical tractability rather than strong prior information, empirical analyses based on such assumptions may be unreliable.

In this article, we present a method for the nonparametric estimation of the determinants of the unemployment duration distribution. This method is designed to be applicable to discrete-time time-series data on gross outflows from different unemployment duration classes. Gross (or aggregate, or macro) data have the advantage that they provide the exact values of the exit probabilities (or exit rates) out of the different duration classes considered (averaged over unobserved heterogeneity).

The model and the estimation method proposed here explicitly take into account that individual exit probabilities are affected by macro effects such as business cycle effects and seasonal effects. The intuition underlying the identification is the following: Assume that the quality of the workers flowing into the first unemployment duration class is stable over time. Now, consider the quality of the workers in the second duration class in two situations: first, a tight labor market with a large outflow; second, a slack labor market with a small outflow. If there is a large outflow, then the best workers leave unemployment sooner than if there is a small outflow. Thus, the quality of the remaining workers in the second duration class is relatively low if there is a tight labor market. So, by comparing different states of the labor market, we are able to learn something about the underlying heterogeneity distribution. This is another advantage over the usual approach in micro econometric studies on unemployment durations. As a by-product, the estimation method presented here can be used to obtain estimates of business-cycle effects and other calendar time effects on unemployment durations. (This however will not be our primary concern here. Also, we will not focus on the composition and changes of the aggregate unemployment rate.)

Section II presents the model and the estimation method. Basically, the model is an MPH model in which calendar time replaces the role of the observed explanatory (x) variables. The estimation method generalizes the method proposed in Van Ours (1992). It enables one to estimate the quantities of interest from ratios of observed hazards without the need to parameterize the determinants of the hazards. In Section II we also develop specification tests to test for the MPH specification, and we extend the model to allow for seasonal effects in the inflow into unemployment. (It should be noted from the outset that, in principle, the method proposed can also be applied for the analysis of other duration variables.)

We apply the estimation method to Current Population Survey (CPS) unemployment duration data from the U.S. Bureau of Labor Statistics. Section III describes the data in some detail. Section IV contains the results. In some respects, unemployment dynamics in the United States differ greatly between individuals with different sex and race characteristics. It would be too restrictive to assume that the duration dependence and calendar-time dependence patterns are the same for all four groups that can be distinguished. The data are disaggregated over these groups, so the empirical analysis is carried out separately for each group. It turns out that the duration dependence patterns and the distributions of unobserved heterogeneity differ between groups with different sex/race characteristics. Section V concludes.

II. The Model and the Estimation Method

A. Model Assumptions

In this subsection we present the unemployment duration model and the underlying assumptions. In subsections IIB–IID we then examine what can be inferred about the model from aggregate data on exit probabilities out of unemployment. An estimation strategy is proposed that enables us to estimate the quantities of interest. Recall that our inferences are purely nonparametric. That is, we do not parameterize the model, and, strictly speaking, we estimate (summary measures of) functions rather than parameters.

We use two measures of time, each with a different origin. The variable t denotes the duration of unemployment for a given individual, as measured from the moment the individual becomes unemployed. The variable τ denotes calendar time, which has its origin somewhere in the past. For simplicity we take t and τ to have the same measurement scale (apart from the difference in origin). Both t and τ are discrete variables. As an example, consider an individual who is unemployed for t periods at calendar time τ. If he fails to leave unemployment in period t, he will be unemployed for $t + 1$ periods at calendar time $\tau + 1$.

For a good understanding of the model and the estimation method, it is useful to have an idea of the type of data for which this is all designed to be applicable to. Ideally, aggregate data give the total numbers of individuals in the labor market who are unemployed for t periods of time ($t = 0, 1, 2, \ldots$) at calendar times τ ($\tau = \tau_0, \tau_0 + 1, \tau_0 + 2, \ldots$). By comparing the number of individuals who are unemployed for t periods of time at τ to the number unemployed for $t + 1$ periods at $\tau + 1$, we observe the fraction of the former who leave unemployment at τ. This fraction, of course, equals the probability that a randomly chosen individual who is unemployed for t periods leaves unemployment, when calendar time equals τ at the moment of potential exit. So, we observe these exit probabilities for different values of t and τ.

The model for these exit probabilities expresses them in terms of the (determinants of the) exit probabilities at the individual level. The relation is established by way of aggregating over individual unemployment duration distributions. It is assumed that all variation in the individual exit probabilities out of unemployment can be explained by the prevailing unemployment duration t and calendar time τ and by observed and unobserved heterogeneity across individuals. The effect of t represents genuine duration dependence, that is, dependence of individual exit probabilities on the elapsed unemployment duration. Calendar time is assumed to capture macro effects (including business cycle and seasonal effects) on individual exit probabilities, as well as structural changes influencing these probabilities.

Usually, aggregate unemployment data do not contain much information on individual characteristics that could be used as explanatory variables x. At best, the data are stratified into a small number of different types of individuals. We estimate the model separately for each type, so in the sequel we suppress the conditioning on the prevailing value of x.

We denote the probability that an individual leaves unemployment right after t periods of unemployment, given that he is unemployed for t periods at calendar time τ, and conditional on his unobserved characteristics v, by $\theta(t \mid \tau, v)$. The unemployment duration density conditional on calendar time and conditional on v can be constructed from these individual exit probabilities. For example, the probability that unemployment duration equals t, when calendar time was $\tau - t$ at the moment of inflow into unemployment, conditional on v, equals

$$\theta(t \mid \tau, v) \cdot \prod_{i=1}^{t} [1 - \theta(t - i \mid \tau - i, v)] \tag{1}$$

for all $t \in \{0, 1, \ldots\}$. We take the product term to be one if $t = 0$.

We make the following assumptions.

ASSUMPTION 1. MPH: $\theta(t \mid \tau, v)$ has a mixed proportional hazard specification; that is, there are functions ψ_1 and ψ_2 such that

$$\theta(t \mid \tau, v) = \psi_1(t) \cdot \psi_2(\tau) \cdot v, \tag{2}$$

with ψ_1 and ψ_2 positive and uniformly bounded from above. Further, the distribution of v is such that, for every t and τ,

$$\mathrm{pr}(0 < \theta(t \mid \tau, v) < 1) = 1.$$

ASSUMPTION 2. Independence of v and τ: the distribution of v in the inflow into unemployment does not depend on the moment of inflow (this part will be relaxed later on). Further, the individual level of v does not change during unemployment.

ASSUMPTION 3. Variation over calendar time: the function ψ_2 is not constant.

The functions ψ_1 and ψ_2 represent the duration dependence and the calendar time dependence of the individual exit probabilities out of unemployment. As we will see, assumptions 1–3 ensure nonparametric identifiability of the model. In particular, they ensure that duration dependence and unobserved heterogeneity can be distinguished empirically.

Assumption 1 is reminiscent of the standard MPH assumption in reduced-form models for micro duration data (see Lancaster [1990] for an extensive survey of such models). In models for micro duration data, dependence on calendar time is usually ignored, and the role of τ in the model above is replaced by the role of observed explanatory variables x. Elbers and Ridder (1982) prove that the latter type of models are nonparametrically identified if assumptions similar to those above are satisfied. Whenever calendar time is included as a regressor in reduced-form duration models for micro data, it is usually included as a multiplicative term in the hazard rate (see, e.g., Imbens 1991).

An important difference between the present model and MPH models for micro data is that here we have discrete time, whereas in micro studies time is usually treated as continuous. Note that the present model is not the discretized (i.e., grouped) version of the continuous-time MPH model (see, e.g., Meyer 1990; and McCall 1994). Indeed, the present model should not be interpreted as an approximation to the continuous-time MPH model. Rather, it should be regarded as a flexible accounting device for discrete aggregate duration data, with an appealing interpretation. Still, as shown below, certain identification features of the present model are the same as those of the continuous-time MPH model.

Because of the discrete-time framework, we had to introduce the last line of assumption 1. Note that it implies that the support of v is bounded. This in turn implies that all moments of v exist.

B. Observed Exit Probabilities

As mentioned above, the data provide observations on the probabilities that individuals leave unemployment when being unemployed for t periods, when calendar time equals τ at the moment of exit, for different values of t and τ. These probabilities are unconditional on the unobserved heterogeneity term v and will be denoted by $\theta(t\,|\,\tau)$. In this subsection we express these $\theta(t\,|\,\tau)$ in terms of the individual exit probabilities $\theta(t\,|\,\tau, v)$ and their determinants. The situation is similar to reduced-form analyses of micro duration data in which the model expresses the exit probabilities conditional on observed and unobserved explanatory variables, but the data provide information only on exit probabilities conditional on the observed variables.

Let $\boldsymbol{t}$ denote the random unemployment duration and t its realization. In obvious notation, it holds that

$$\begin{aligned}\theta(t\,|\,\tau) &\equiv \frac{\mathrm{pr}(\boldsymbol{t} = t\,|\,\text{inflow at } \tau - t)}{\mathrm{pr}(\boldsymbol{t} \geq t\,|\,\text{inflow at } \tau - t)} \\ &= \frac{E_v(\mathrm{pr}(\boldsymbol{t} = t\,|\,\text{inflow at } \tau - t;\, v))}{E_v(\mathrm{pr}(\boldsymbol{t} \geq t\,|\,\text{inflow at } \tau - t;\, v))},\end{aligned} \tag{3}$$

in which $\mathrm{pr}(\boldsymbol{t} = t\,|\,\text{inflow at } \tau - t;\, v)$ and $\mathrm{pr}(\boldsymbol{t} \geq t\,|\,\text{inflow at } \tau - t;\, v)$ can be expressed in terms of $\theta(t\,|\,\tau, v)$ (note that eq. [1] gives $\mathrm{pr}(\boldsymbol{t} = t\,|\,\text{inflow at } \tau - t;\, v)$). By doing this, and by substituting equation (2), we get

$$\theta(t \mid \tau) = \frac{\psi_1(t) \cdot \psi_2(\tau) \cdot E_v\left[v \cdot \prod_{i=1}^{t} [1 - \psi_1(t-i) \cdot \psi_2(\tau - i) \cdot v]\right]}{E_v\left[\prod_{i=1}^{t} [1 - \psi_1(t-i) \cdot \psi_2(\tau - i) \cdot v]\right]}. \tag{4}$$

Thus, $\theta(t \mid \tau)$ can be expressed in terms of the "structural functions" ψ_1, ψ_2, and the distribution function $G(v)$ of v. In fact, we can be more specific on the way $G(v)$ enters such expressions. By expanding the products in the right-hand side (r.h.s.) of (4), it follows that $\theta(t \mid \tau)$ depends on $G(v)$ only by way of the first $t + 1$ moments of v. Denote $E_v(v^i)$ by μ_i. We have the following result: $\theta(t \mid \tau)$ depends on $\{\psi_1(i), \psi_2(\tau - t + i), \mu_{i+1}$, with $i = 0, 1, \ldots, t\}$. We will call the elements of the latter set the "parameters," even though they really are values of functions on $\mathbb{N}$ and summary statistics of the underlying heterogeneity distribution, respectively.

If we observe $\theta(t \mid \tau)$ for a large number of values of τ and t, then the number of observations exceeds the number of unknown parameters. Suppose we observe $\theta(t \mid \tau)$ for $\tau \in \{T + 1, T + 2, \ldots, T + n_\tau\}$ and for $t \in \{0, 1, \ldots, n_t - 1\}$. We then have $n_t \cdot n_\tau$ observations. The number of parameters in the expressions for the observed exit probabilities equals $3n_t + n_\tau - 1$ (namely, n_t moments of v, n_t terms $\psi_1(0) \ldots \psi_1(n_t - 1)$, n_τ terms $\psi_2(T + 1) \ldots \psi_2(T + n_\tau)$, and $n_t - 1$ terms $\psi_2(T - n_t + 2) \ldots \psi_2(T)$). From equation (2) it follows that two parameters can be normalized arbitrarily. As a result, the number of observations minus the number of remaining parameters equals $(n_t - 1) \cdot (n_\tau - 3)$. This is positive if $n_t > 1$ and $n_\tau > 3$.

Consequently, it seems that all parameters can be estimated from a sufficiently large sample. (For the moment, we are silent on exactly how the parameters should be estimated. The idea is that each observed exit probability $\theta(t \mid \tau)$ should be as close as possible to the model expression corresponding to it.) However, in typical data settings, the number of duration classes on which reliable data are available is fixed and relatively small, while the number of calendar time points on which information is available is large. Then the number of observations containing information on any particular term $\psi_2(\tau)$ is small, so the estimate of it would be unreliable. Moreover, the number of such terms increases linearly with the number of calendar time points; that is, the number of parameters increases linearly with the sample size. However, note that we are primarily interested in estimating the duration dependence and unobserved heterogeneity parameters. For this, the calendar time dependence parameters are nuisance parameters. Thus, it would be nice if the parameters of interest could be estimated without the need to deal with the calendar time dependence parameters.

It turns out that the ideas in Van Ours (1992) can be extended and applied to achieve this aim. Basically, these ideas amount to substituting values of past observed exit probabilities into the expressions (4) for $\theta(t \mid \tau)$

and examining ratios of the resulting expressions for different t. We illustrate this in the next subsections.

C. A Preliminary Application

To explain the gist of our method, we present a preliminary application using exit probabilities for the first 2 months of U.S. unemployment. Consider expression (4) for $t = 0$ and $t = 1$:

$$\theta(0 \mid \tau) = \psi_1(0) \cdot \psi_2(\tau) \cdot \mu_1, \tag{5}$$

and

$$\theta(1 \mid \tau) = \frac{\psi_1(1) \cdot \psi_2(\tau) \cdot [\mu_1 - \psi_1(0) \cdot \psi_2(\tau - 1) \cdot \mu_2]}{1 - \psi_1(0) \cdot \psi_2(\tau - 1) \cdot \mu_1}. \tag{6}$$

Substituting a 1-period lagged version of (5) into (6), we obtain

$$\theta(1 \mid \tau) = \psi_1(1) \cdot \psi_2(\tau) \cdot \mu_1 \frac{1 - (\mu_2/\mu_1^2) \cdot \theta(0 \mid \tau - 1)}{1 - \theta(0 \mid \tau - 1)}. \tag{7}$$

We can eliminate $\psi_2(\tau)$ by taking the ratio of (7) and (5). Denoting (μ_2/μ_1^2) by γ_2 and $\psi_1(1)/\psi_1(0)$ by η_1, we get

$$\frac{\theta(1 \mid \tau)}{\theta(0 \mid \tau)} = \eta_1 \cdot \frac{1 - \gamma_2 \cdot \theta(0 \mid \tau - 1)}{1 - \theta(0 \mid \tau - 1)}. \tag{8}$$

It holds that $\theta(1 \mid \tau)/\theta(0 \mid \tau)$ depends on $\theta(0 \mid \tau - 1)$ if and only if $\gamma_2 \neq 1$, which in turn holds if and only if there is unobserved heterogeneity (note that $\gamma_2 = 1 + \text{var}(v)/\mu_1^2$ and that always $\gamma_2 \geq 1$). The exit probability $\theta(0 \mid \tau - 1)$ varies with τ by virtue of assumption 3, so, in sum, $\theta(1 \mid \tau)/\theta(0 \mid \tau)$ varies with τ if and only if there is unobserved heterogeneity. Clearly, η_1 and γ_2 are identified.

To estimate γ_2 and η_1 from (8) we use information about the first two monthly exit probabilities out of U.S. unemployment. As we describe in section III, we have this information for the period 1967–91. We also account for seasonal effects in the composition of the inflow in the way described in subsection IID. In this preliminary empirical analysis we adopt the following regression-type stochastic specification: log $\theta(1 \mid \tau)/\theta(0 \mid \tau)$ equals the log of the r.h.s. of (8), plus an error term. This error term is assumed to represent an independently and identically distributed (i.i.d.) specification error. We then estimate the parameters using nonlinear regression. The results for the relevant parameters (and standard errors) are

$$\gamma_2 = 1.108\ (0.015)$$

and

$$\eta_1 = 0.939\ (0.020).$$

What do we learn from this? First, the heterogeneity parameter γ_2 is significantly larger than one, which implies $\text{var}(v) > 0$, so unobserved heterogeneity is present. Second, the duration dependence parameter η_1 is significantly smaller than one. This implies that the average individual exit probability decreases from the first to the second month of unemployment, so there is negative duration dependence in the first 2 months of U.S. unemployment.

D. Generalization

In this subsection we generalize the model as well as the empirical approach discussed above. In particular, we introduce the use of information on higher duration classes and pay attention to the effects of seasonal fluctuations on the exit probabilities. We start with the former.

Analogous to the derivation of (8), we can derive general expressions for ratios of exit probabilities for two consecutive duration classes at the same calendar time point. Denote μ_i/μ_1^i by γ_i $(i \geq 2)$ and $\psi_1(t)/\psi_1(t-1)$ by η_t $(t \geq 1)$. The parameters η_t represent the duration dependence of the exit probability as a function of t, whereas the parameters γ_i represent the normalized moments of the distribution of unobserved heterogeneity. Then, the ratio $\theta(t\,|\,\tau)/\theta(t-1\,|\,\tau)$ can be written as

$$\begin{aligned}\frac{\theta(t\,|\,\tau)}{\theta(t-1\,|\,\tau)} = \eta_t \cdot \{&\text{expression depending on } \theta(i-1\,|\,\tau-t+i-1) \\ &\text{and } \gamma_{i+1} \text{ with } i = 1, 2, \ldots, t, \text{ and, if } t \geq 2, \\ &\text{on } \theta(i-1\,|\,\tau-t+i) \text{ with } i = 1, 2, \ldots, t-1\}.\end{aligned} \tag{9}$$

For $t \geq 2$, the expressions at the r.h.s. of (9) are quite lengthy. However, it is straightforward to calculate the exact value of $\theta(t\,|\,\tau)/\theta(t-1\,|\,\tau)$ numerically once its determinants are quantified. Also, note that the expressions are recursive in $\theta(t\,|\,\tau)$.

These ratios of observed exit probabilities can be used to estimate the parameters of interest. In doing so, we deal with the problems encountered in subsection IIB. Note that (9) does not depend on the nuisance parameters of ψ_2 anymore and that the number of parameters does not increase when the number of calendar time points in the data (i.e., the sample size) increases. Moreover, for each parameter η_t and γ_i, the number of observations that contain information on it is considerable. This can be clarified by examining ratios $\theta(t \mid \tau)/\theta(t-1 \mid \tau)$ recursively, starting with $t = 1$. Suppose that, as in the previous subsection, we have $n_t \cdot n_\tau$ observed exit probabilities. Let $n_\tau \geq n_t \geq 2$. As shown in the previous subsection, we can estimate η_1 and γ_2 from the data on $\theta(1 \mid \tau)/\theta(0 \mid \tau)$. This amounts to estimating two parameters from $n_\tau - 1$ ratios of observed exit probabilities. Now consider (9) for $t = 2$:

$$\frac{\theta(2 \mid \tau)}{\theta(1 \mid \tau)} = \eta_2 \cdot \frac{1 - \theta(0 \mid \tau - 1)}{[1 - \theta(1 \mid \tau - 1)] \cdot [1 - \theta(0 \mid \tau - 2)]} \cdot \frac{\begin{array}{c} 1 - \gamma_2 \cdot \theta(0 \mid \tau - 2) - \theta(1 \mid \tau - 1) \cdot [1 - \theta(0 \mid \tau - 2)] \\ \times \{[\gamma_2 - \gamma_3 \cdot \theta(0 \mid \tau - 2)]/[1 - \gamma_2 \cdot \theta(0 \mid \tau - 2)]\} \end{array}}{1 - \gamma_2 \cdot \theta(0 \mid \tau - 1)}. \tag{10}$$

Given the estimate of γ_2, we can estimate η_2 and γ_3 from the data on $\theta(2 \mid \tau)/\theta(1 \mid \tau)$. This amounts to estimating two parameters from $n_\tau - 2$ ratios of observed exit probabilities, and so on. Note that the number of parameters cannot be reduced further by normalizations since η_t and γ_i are defined as ratios of the original parameters. Also, note that an estimation method based on recursive examination of ratios of observed exit probabilities is not efficient, since γ_i enters the expression of $\theta(t \mid \tau)/\theta(t-1 \mid \tau)$ for every $t \in \{i-1, i, \ldots\}$.

In any case, for typical values of n_τ, the parameters of interest are estimable reliably by using (9). The estimates of $\eta_1, \eta_2, \ldots$ show the evolution of the duration dependence of the exit probability $\theta(t \mid \tau, v)$. The estimates of $\gamma_2, \gamma_3, \ldots$ give information on the distribution of unobserved heterogeneity. We return below to the issue of recovering $G(v)$ from $\gamma_2, \gamma_3, \ldots$.

The parameters are estimated as follows. We specify log $\theta(t \mid \tau)/\theta(t-1 \mid \tau)$ to equal the log of the corresponding model expression, plus an error term. The error terms represent specification errors that are identically distributed over equations and over observations. As in the preliminary application in subsection IIC, we assume that the errors in a given equation are independent across the observations (this will be tested below). However, we allow the errors in different equations to be contemporaneously related. So, at a given point of calendar time, the specification errors for different ratios of exit probabilities may be related. We do not make a parametric assumption on the distribution of the error terms. The estimation method we employ is seemingly unrelated nonlinear regression (SUNR).

Let us return to the ratios $\theta(t \mid \tau)/\theta(t-1 \mid \tau)$. If there is no unobserved heterogeneity, then $\theta(t \mid \tau)/\theta(t-1 \mid \tau) = \eta_t$, so these ratios do not depend on τ. (This can be checked in [10] by noting that in that case $\mu_i = \mu_1^i$ for every $i \geq 1$, so $\gamma_i = 1$.) If there is unobserved heterogeneity, then in general these ratios do depend on τ (recall the discussion of eq. [8]). The ratio $\theta(t\,|\,\tau)/\theta(t-1\,|\,\tau)$ can be thought of as the discrete-time equivalent of the derivative of log $\theta(t\,|\,\tau)$ with respect to t. Thus, we are able to identify the parameters associated with the distribution of unobserved heterogeneity from the interaction terms (or cross effects) of t and τ in log $\theta(t\,|\,\tau)$. (There is an analogy with continuous-time MPH models in which the role of τ is replaced by observed regressors x; see Van den Berg [1992]; and Melino and Sueyoshi [1990].) Clearly, the MPH assumption is crucial for this. It is therefore important to test any overidentifying aspects of that assumption. The next subsection deals with this.

In general, the interaction between t and τ in the observed exit probabilities that is caused by unobserved heterogeneity is such that the observed degree of duration dependence is less negative in a recession than at the top of the business cycle. For example, equation (8) implies that, if $\gamma_2 > 1$ and $\eta_1 < 1$, the decrease of $\theta(t\,|\,\tau)$ when going from $t = 0$ to $t = 1$ is smaller in a recession ($\theta(0\,|\,\tau - 1)$ small) than at the top of the cycle ($\theta(0\,|\,\tau - 1)$ large). This is because in a recession the weeding out of individuals with a high quality (i.e., a large v) cannot occur as fast as in the other case. Note that the model implication on the interaction sign is testable. In particular, if $\gamma_2 < 1$, then the interaction sign in (8) is opposite to above.

One may distinguish two types of seasonal effects on the exit probabilities. First, there may be an effect that equally affects every unemployed individual. For example, there may be less activity on the labor market during the holiday season. Second, there may be a permanent effect of the season prevailing at the moment of inflow into unemployment. For example, the success of individuals in the inflow at the end of the schooling season may on average be different from that at other times of the year. This may be labeled the cohort effect. If the unit of time period is sufficiently small, then the first effect is captured by the $\psi_2(\tau)$ terms in the model. So far we have ignored the second effect. To incorporate it, we allow for dependence of $G(v)$ on the moment of inflow, so we model the composition of the inflow to be dependent on the season at the moment of inflow.

For the moment, suppose there are two seasons, labeled by indices A and B. We assume that the season at the moment of inflow affects a scale parameter of the distribution of unobserved heterogeneity in the inflow,

$$G_{\mathrm{B}}(v) = G_{\mathrm{A}}(\omega \cdot v), \tag{11}$$

with $\omega > 1$, so A is the "good" season and B is the "bad" season. (It can be shown that this is observationally equivalent to assuming that $\theta(t\,|\,\tau, v)$ contains a fourth multiplicative term depending on the season prevailing at the moment of inflow.) As a result, $\mu_{i,\mathrm{A}} = \omega^i \cdot \mu_{i,\mathrm{B}}$ and $\mu_{i,\mathrm{A}}/\mu_{1,\mathrm{A}}^i = \mu_{i,\mathrm{B}}/\mu_{1,\mathrm{B}}^i$. The latter ratio is denoted by γ_i.

In this model, all moments entering the expression for $\theta(t|\tau)$ that corresponds to (4) are moments of the heterogeneity distribution for the season at $\tau - t$. It can be shown that the expressions for the ratios of observed exit probabilities differ in a very simple way from the corresponding expressions (9) for the basic model. If $\tau - t$ is a bad season but $\tau - t + 1$ is a good season, then $\theta(t|\tau)/\theta(t-1|\tau)$ is equal to a factor $1/\omega$ times the corresponding expression in subsection IIC. If $\tau - t$ is a good season but $\tau - t + 1$ is a bad season, then $\theta(t|\tau)/\theta(t-1|\tau)$ is equal to a factor ω times the corresponding expression in subsection IIC. If $\tau - t$ and $\tau - t + 1$ are in the same season, then $\theta(t|\tau)/\theta(t-1|\tau)$ equals the corresponding expression in subsection IIC.

This method can be generalized to more than two seasons. In fact, the duration of a season may be taken to equal the unit of time. For example, if monthly data are observed, then we may distinguish 12 seasons corresponding to the months of the year. Let $s \in \{1, 2, \ldots, 12\}$ denote the number of the month, and let G_s denote the distribution function of v in the inflow into unemployment at month s. Analogous to (11), we postulate that

$$\left.\begin{aligned} &G_1(v) = G_{12}(\omega_1 \cdot v), \\ &G_s(v) = G_{s-1}(\omega_s \cdot v) \quad s \in \{2, 3, \ldots, 11\}, \\ \text{and}\quad & \\ &G_{12}(v) = G_{11}(v/(\omega_1 \cdot \omega_2 \ldots \omega_{11})). \end{aligned}\right\} \tag{12}$$

Thus, we have 11 additional parameters. Again, these appear as multiplicative factors in the expressions for the ratios of the hazards. In conclusion, the analysis can easily be extended to allow for seasonal (or cohort) effects, which can be estimated along with the other parameters.

Alternatively, one might want to model a calendar time trend in $G(v)$ by assuming that $G(v)$ at τ equals $G(\omega \cdot v)$ at $\tau - 1$, for every τ. However, it can be shown that this would make the η_t parameters unidentified.

E. Specification Tests

The model specification can be tested in a number of ways. First of all, consider the estimates of $\gamma_2, \ldots, \gamma_{n_t}$. Let us normalize by taking $\mu_1 = 1$, so γ_i equals $E(v^i)$. The fact that the support of $G(v)$ is positive restricts the set of admissible values of $\gamma_2, \ldots, \gamma_{n_t}$. Since these restrictions are not imposed when estimating the model, we can test for them. Suppose for example that $n_t = 3$. No distribution with positive support is able to generate moments satisfying $\gamma_2 < 1$ or $\gamma_3 < \gamma_2^2$ (see Shohat and Tamarkin 1970; e.g., $\gamma_2 < 1$ would imply $\mathrm{var}(v) < 0$). If $\gamma_2 \geq 1$ and $\gamma_3 \geq \gamma_2^2$ then, in contrast, there are such distributions, except when $\gamma_2 = 1$ and $\gamma_3 > 1$. So, a relatively simple procedure is to test $\gamma_2 \geq 1$ and $\gamma_3 \geq \gamma_2^2$

versus their opposites. If $n_t = 4$ then an additional necessary condition for the specification to be correct is that $(\gamma_4 - \gamma_2^2) \cdot (\gamma_2 - 1) - (\gamma_3 - \gamma_2)^2 \geq 0$ (see Shohat and Tamarkin 1970).

If these tests do not result in rejections, then one can usually find a discrete distribution with a finite number of points of support that is able to generate the γ_i estimates (see Shohat and Tamarkin 1970; and Lindsay 1989). Lindsay (1989) provides formulas for recovering such a discrete distribution from the moments. It should be noted that in general there will also be nondiscrete distributions that are able to generate a given finite set of moments. Consequently, if the estimated γ_i are moments of some distribution, then in general there will be more than one distribution function $G(v)$ consistent with them.

The moment tests proposed above are informative on the validity of assumption 1. Suppose that in reality $\theta(t \mid \tau, v)$ is not multiplicative in t, τ, and v, but instead contains interaction terms. Then, in particular cases, this shows up in the γ_i estimates being inconsistent with the moment restrictions above. For example, suppose that the duration dependence pattern for individuals with large v differs from that for individuals with small v, in the following way: $\theta(t \mid \tau, v) = \psi_1(t, v) \cdot \psi_2(\tau)$, with $\psi_1(0, v) = v$ and $\psi_1(1, v) = 1/v$. It can be shown that then the estimate of γ_2 asymptotically is smaller than one. Also, recall the discussion in the previous subsection on the sign of the interaction between t and τ in the observed exit probabilities. Finally, the tests may detect misspecification of the unit of time period (e.g., if in reality the model is correct for weekly periods but it is assumed to be correct for monthly periods).

The model specification can also be tested by adding terms depending on τ and containing a multiplicative parameter (like $\xi\tau$) to the right-hand sides of equations (9) and testing whether such parameters equal zero ($\xi = 0$). We also perform extensive residual analyses. Finally, we estimate the model for subsamples distinguished by their range of values of τ and compare the results. Such a procedure may be interpreted more positively as making the results less sensitive to structural changes, like long-run trends in the composition in the inflow.

It should be noted that there are alternative models that are observationally equivalent to our model, and that therefore cannot be detected by any test. A trivial example is the ad hoc non-MPH model in which individual exit probabilities are given by equations such as (5) and (6) and in which there is no unobserved heterogeneity.

III. The Data Set

In our empirical analysis we use unpublished CPS data from the U.S. Department of Labor which give monthly information on unemployment by weekly duration classes. The data are based on monthly large-scale surveys. We use information for the period 1967–91. Analyzing unemployment durations by using CPS data has been popular for some time.

Some studies use information on in-progress spells of unemployment to estimate the distribution of the durations of completed spells, relying on steady-state assumptions (see, e.g., Butler and McDonald 1986). Sider (1985) and Baker (1992*a*) relax the steady-state assumption. In our framework, cohorts are distinguished by the value of τ at the moment of inflow into unemployment, so no steady-state assumption is needed.

As, for example, Sider (1985) and Baker (1992*a*) point out, there are several problems connected with the use of CPS data for unemployment duration analyses. First of all, the data are not based on cohorts of individuals who are followed until they leave unemployment. The set of sampled individuals changes substantially between any 2 consecutive months. However, we may consider the data as synthetic cohorts, even more so because the sample size is much larger than typically encountered in micro data sets. Still, when we do so, the data generate a small number of inconsistent (< 0, or very small) monthly exit probabilities. In some cases this led to very large ratios $\theta(t \mid \tau)/\theta(t - 1 \mid \tau)$. We therefore skipped observations for which $\theta(t \mid \tau)$ was smaller than 0.05. This restriction is arbitrary, but the use of similar restrictions with different boundaries did not lead to substantially different results.

The way we use the data prohibits a distinction between employment as destination and departure from the labor force as alternative destination. But, as Abowd and Zellner (1985) show, the share in the outflow from unemployment of workers becoming employed is larger than that of workers leaving the labor force.

A second potential problem concerns the fact that we need data in which the frequency with which the data are collected equals the sizes of the unemployment duration classes. This implies that we have to aggregate the weekly duration classes into monthly duration classes. Finally, the data are influenced by phenomena like digit preferences and the tendency of respondents to report "weeks of unemployment" as whole months. Because of this we adopted the corrections proposed by Baker (1992*b*) and applied by Baker (1992*a*) and Baker (1992*b*). Baker reallocated 30% of the respondents at 4, 8, 12, 16, and 26 weeks, 40% of those at 52 weeks, and 50% of those at 78 and 99 weeks, in each month of the sample to adjacent later weeks. Since the information on exit probabilities becomes more unreliable at longer durations we used information on exit probabilities only for the first 4 months of unemployment.

In the analysis we use a time series of monthly exit probabilities out of unemployment for four groups of workers: white males, white females, black males and black females.

The CPS data used in Baker (1992*a*) are more disaggregated than those used here, in the sense that the vector of observed individual characteristics x is much larger than here. Baker (1992*a*) investigates whether business cycles affect the aggregate mean unemployment duration mainly by changing the distribution of x in the inflow into unemployment, or mainly by changing the exit probabilities for all unemployed individuals simultaneously. In terms of our model, this amounts to distinguishing whether τ affects the mean unemployment duration because $G(v)$ varies with the moment of inflow τ, or because ψ_2 varies with τ. Baker (1992*a*) finds no evidence for the former phenomenon. This result is confirmed by Imbens and Lynch (1992), who use micro data. This supports our assumption that $G(v)$ does not depend on τ, at least to the extent in which τ represents the business cycle.

Figure 1 shows the developments of the yearly averages of the monthly exit probabilities. Apart from cyclical fluctuations, the exit probability for the first month declines over the 1970s, is stable over the 1980s, and declines again in the beginning of the 1990s. The exit probabilities for the second, third, and fourth month of unemployment are lower and show more fluctuations. For white male workers, the exit probabilities follow a monotone sequence from high to low. For the other groups of workers, in particular the groups of black workers, the exit probability for a higher duration class is sometimes larger than that for a lower duration class. The latter phenomenon may reflect behavior, but it may also reflect inaccuracies due to the fact that the data contain relatively small numbers of black individuals who are observed in the higher duration classes.

Figure 1 shows that the exit probabilities out of unemployment are quite high. In the late 1960s, about 90% of the unemployed workers left unemployment within the first quarter. In the 1980s, this was about 75%–85%. It is clear that there are large cyclical fluctuations in the exit probabilities for the first quarter. Furthermore, it appears that the exit probability for females is higher than for males and the exit probability for white workers is higher than for black workers. In 1990, the average exit probability in the first quarter of unemployment was 83% for white male workers, 87% for white female workers, 78% for black male workers, and 84% for black female workers. Finally, it should be noted that the data display considerable variation over the season of inflow and the season of outflow.

It is clear that the four groups that are distinguished have quite different unemployment dynamics characteristics. Also, for each group there have been major changes in gross outflow rates during the period that the data span. The latter justifies assumption 3.

The model of section II predicts that there is unobserved heterogeneity in the unemployment duration distribution if ratios of observed exit probabilities for different duration classes change over calendar time. This prediction can be used to perform a simple eyeball test. From figure 1 it is clear that such ratios do change over calendar time. Thus, we anticipate significant unobserved heterogeneity.

The information about the first four monthly exit probabilities allows us to estimate three equations such as (9) (each $t \in \{1, 2, 3\}$ defines one equation). These contain three heterogeneity parameters (γ_2, γ_3, γ_4) and three duration dependence parameters (η_1, η_2, η_3). Furthermore we allow for seasonal effects as specified in (12), introducing 11 additional parameters $\omega_1, \ldots, \omega_{11}$. The estimation period is 1967.04–1991.12 (year.month).

IV. The Results

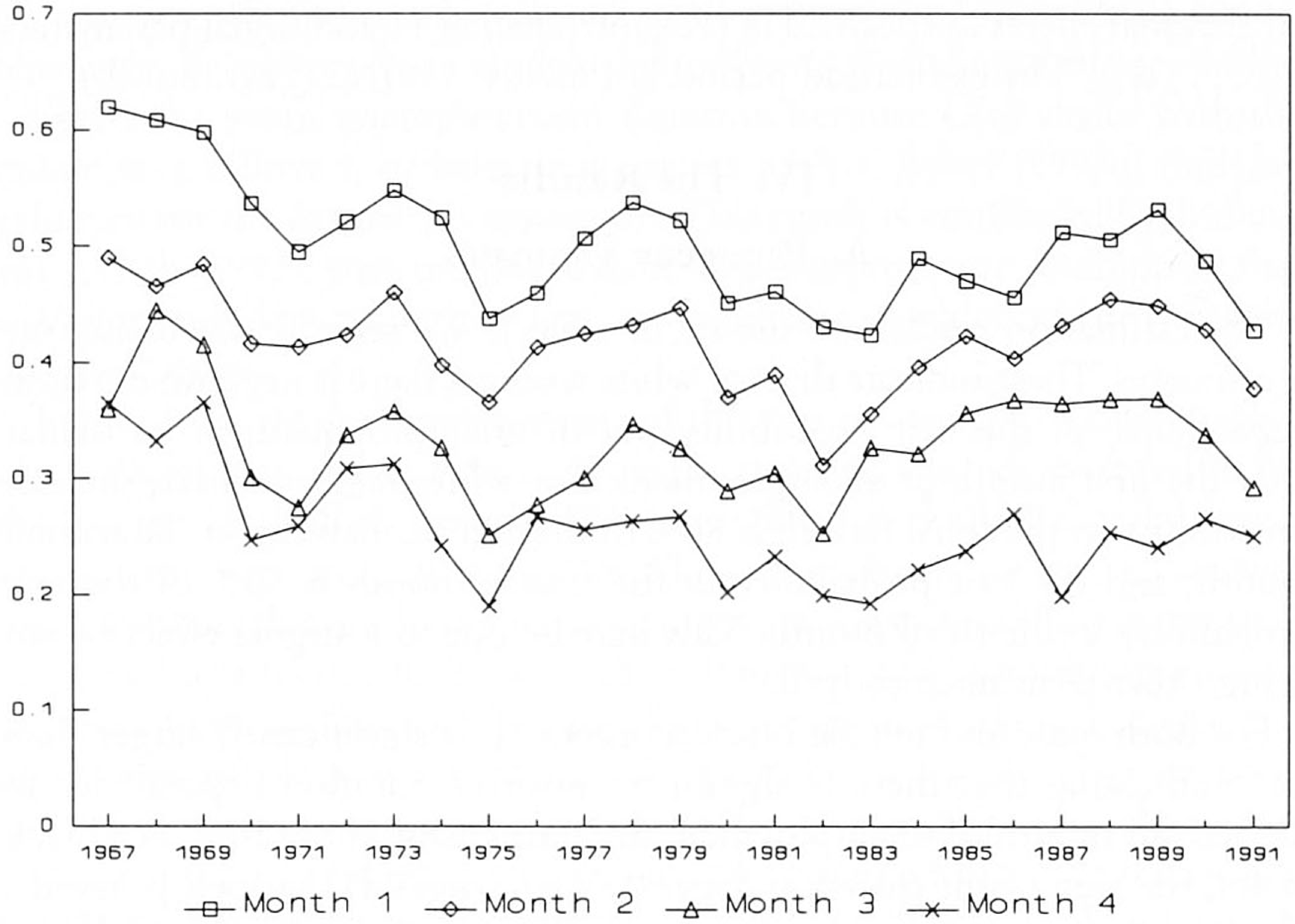
A. Parameter Estimates

The estimation results are shown in table 1. We start by discussing the η_t estimates. These indicate that for white workers there is negative duration dependence of the exit probability out of unemployment, in particular after the first month of unemployment. For white male workers, the exit probability in the third month is 86% of the exit probability in the second month, and the exit probability in the fourth month is 80% of the exit probability in the third month. This may be due to a stigma effect of not being short-term unemployed.

For both male and female black workers, η_1 is significantly larger than one, indicating that there is significant positive duration dependence in the second month of unemployment in comparison to the first. For black males, the sign of the duration dependence changes as the spell proceeds. The less negative duration dependence for blacks (relative to whites) during the first few months can be "explained" in a number of ways (relatively strong anticipation of unemployment benefits exhaustion; relative importance of particular recall options; relatively large nonpecuniary utility of being short-term unemployed; increase in transitions from unemployment to nonparticipation; etc.). However, in the absence of additional information, it is hard to assess the power of such possible explanations. (Note that in the microeconometric literature on unemployment durations it is always assumed that the duration dependence parameters do not depend on individual characteristics like race and gender.)

One potentially interesting explanation for the male difference takes into account that the initial level of the exit probability out of unemployment (i.e., $\theta(0 \mid \tau)$) for black males is on average about 80% of the corresponding level for white males. It may well be that black males carry a stigma from the moment they become unemployed. Now suppose that, in addition to that, in each group, individuals are heavily stigmatized from the moment their spell length is observed by potential employers to belong to the 20% or so longest spells in those groups. Then the duration at which white males start to get a stigma is shorter than the corresponding duration for black males. This may explain the fact that there is more genuine negative duration dependence for white males than for black males, before the fourth month of unemployment duration. If this explanation is correct, then one should expect duration dependence for black males to become more negative after 4 months of unemployment duration.

Equilibrium models of stigma (Berkovitch 1990) seem to predict that the stigmatization of long-term unemployed individuals is stronger if there is more unobserved heterogeneity in the quality of potential em-



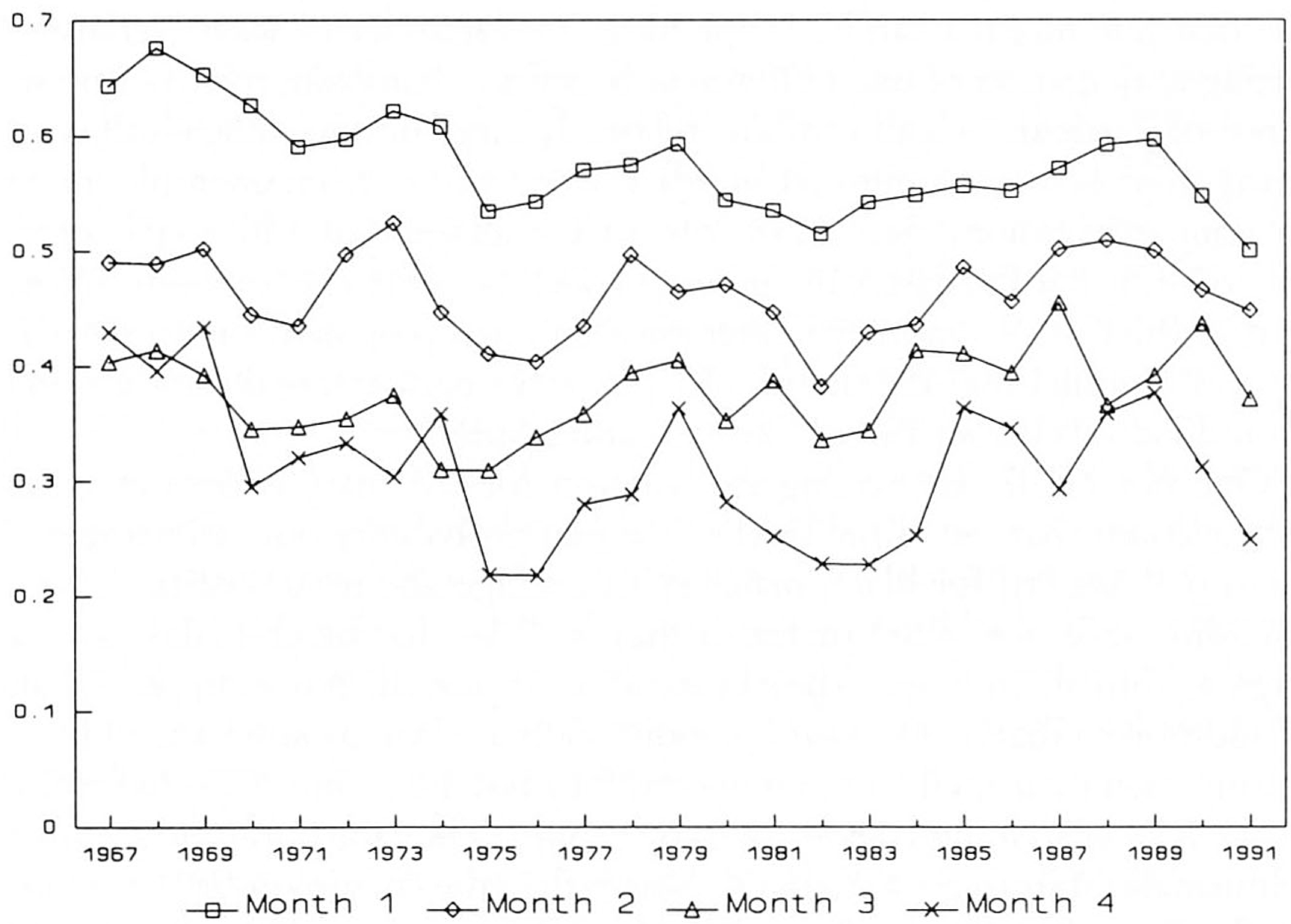
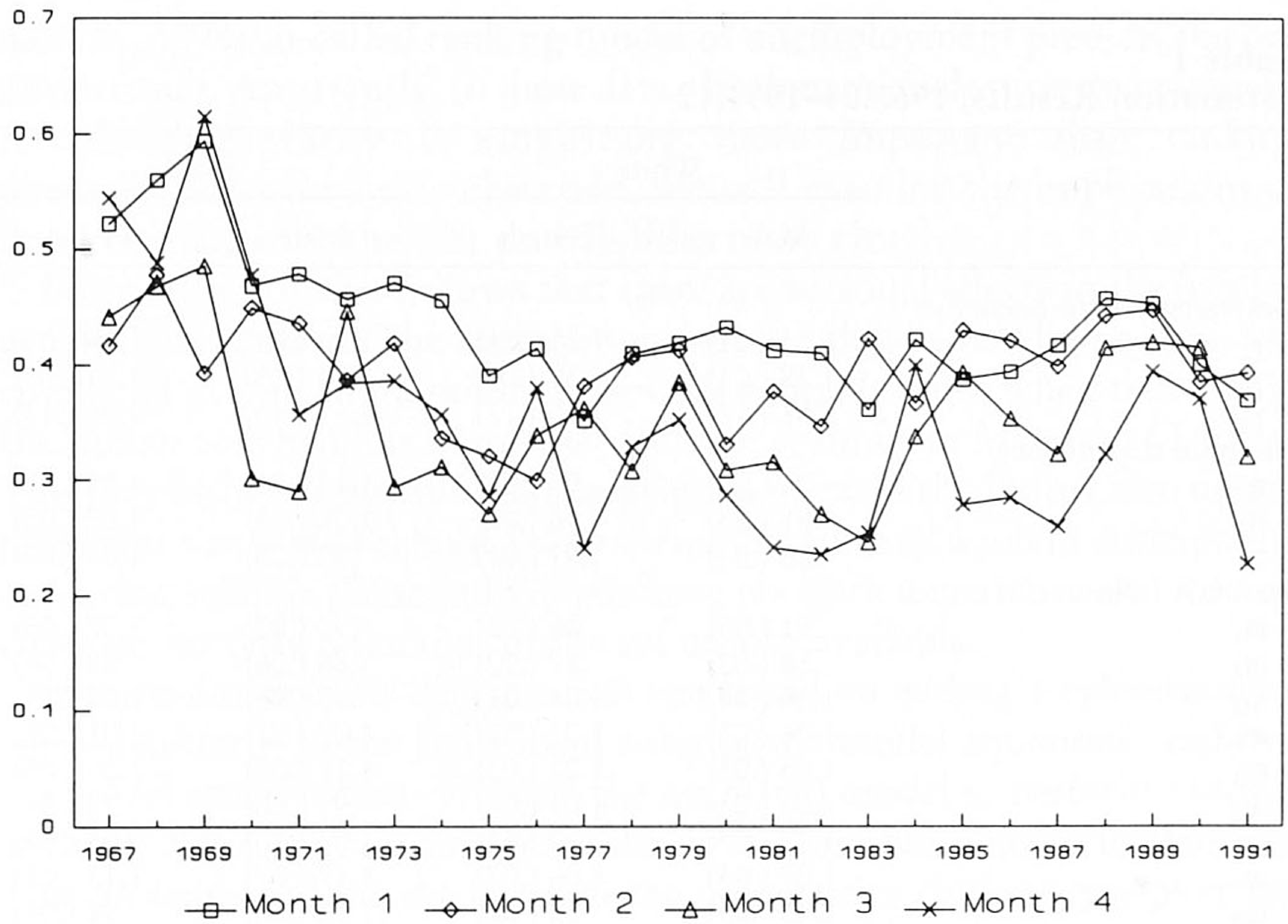


FIG. 1.—Monthly exit probabilities out of unemployment. *a,* White male individuals; *b,* white female individuals; *c,* black male individuals; *d,* black female individuals.

ployer-employee matches. Now suppose that that a large variance of this type of heterogeneity is associated with a large variance of the unobserved heterogeneity in unemployment durations. Then one may expect that, over the four groups we distinguish, a large variance of the



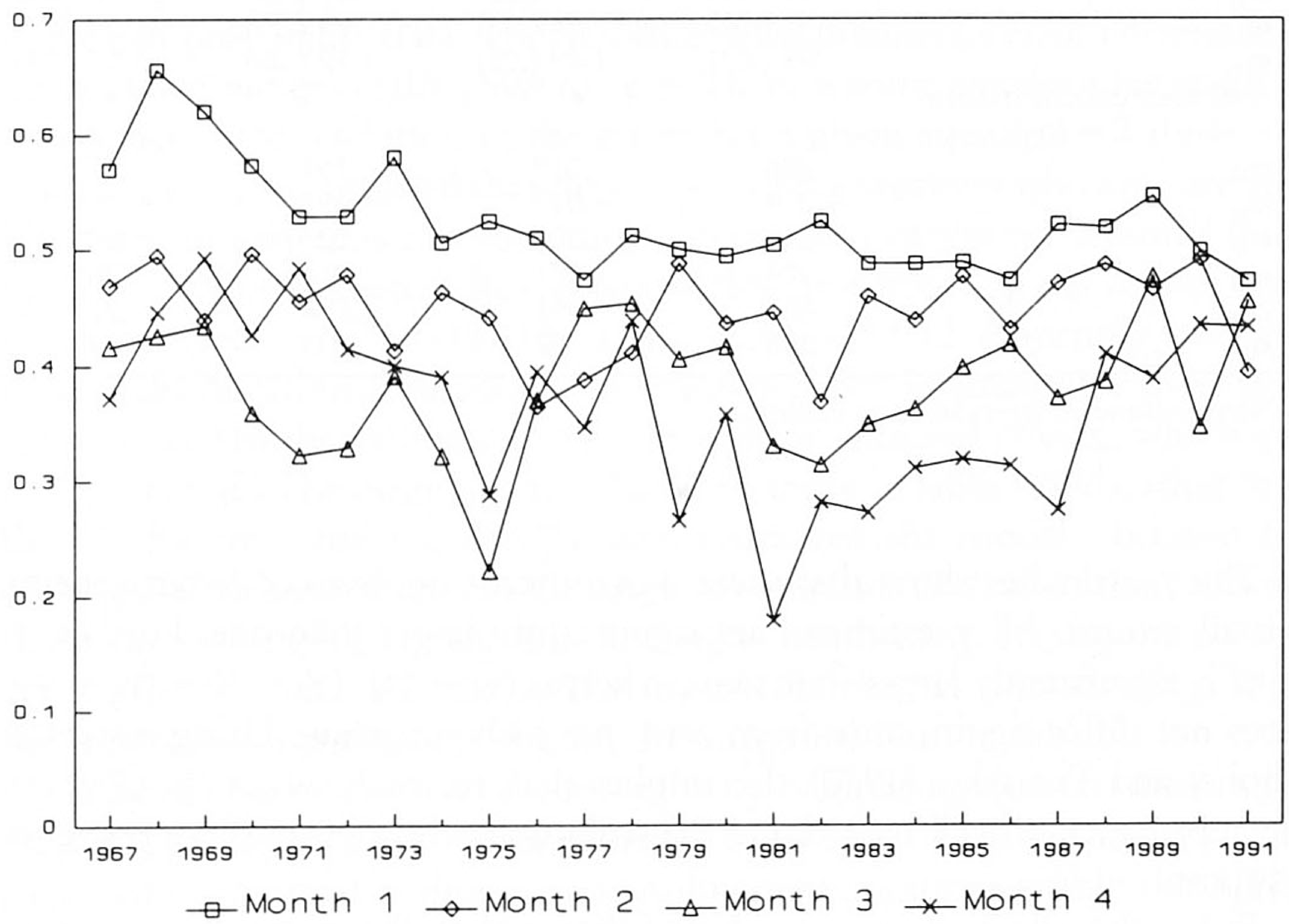


FIG. 1.—(*Continued*)

unobserved heterogeneity distribution is associated with relatively strong negative duration dependence. The results discussed below do not empirically confirm this. Presumably, other differences between these groups are more important.

Table 1
Estimation Results, 1967.04–1991.12

	White		Black	
	Male	Female	Male	Female
Unobserved heterogeneity:				
γ_2	1.13 (.01)	1.11 (.01)	1.24 (.02)	1.19 (.01)
γ_3	1.38 (.04)	1.31 (.05)	1.74 (.05)	1.54 (.05)
γ_4	1.81 (.12)	1.56 (.12)	2.61 (.13)	2.06 (.13)
Duration dependence:				
η_1	.96 (.02)	.95 (.02)	1.12 (.04)	1.08 (.03)
η_2	.85 (.03)	.96 (.03)	1.06 (.05)	1.09 (.05)
η_3	.80 (.03)	.87 (.04)	.92 (.05)	1.01 (.07)
Season at inflow:				
ω_1	.91 (.03)	.86 (.02)	.90 (.07)	1.07 (.05)
ω_2	.86 (.02)	.87 (.02)	.86 (.06)	.82 (.04)
ω_3	1.06 (.03)	1.04 (.02)	.97 (.06)	1.04 (.05)
ω_4	1.06 (.03)	1.03 (.02)	1.07 (.07)	1.01 (.05)
ω_5	1.05 (.03)	1.03 (.02)	1.17 (.07)	1.09 (.05)
ω_6	1.03 (.03)	1.04 (.02)	.91 (.06)	.95 (.04)
ω_7	1.07 (.03)	.99 (.02)	1.03 (.06)	.95 (.04)
ω_8	1.07 (.03)	1.06 (.02)	1.17 (.07)	1.13 (.05)
ω_9	1.06 (.03)	1.05 (.02)	1.10 (.06)	.98 (.04)
ω_{10}	.95 (.02)	1.03 (.02)	.85 (.06)	.99 (.05)
ω_{11}	.91 (.02)	.95 (.02)	.93 (.07)	.94 (.04)
ω_{12}	.98 (.02)	1.07 (.02)	1.12 (.06)	1.07 (.04)
SUNR residual covariance matrix $\Sigma \equiv (\sigma_{ij})$:				
σ_{11}	.026	.019	.154	.077
σ_{12}	−.014	−.010	−.093	−.065
σ_{13}	−.010	−.000	−.023	−.005
σ_{22}	.104	.071	.274	.265
σ_{23}	−.068	−.055	−.154	−.205
σ_{33}	.260	.237	.403	.541

NOTE.—Standard errors are in parentheses.

The γ_i estimates show that there is significant unobserved heterogeneity, for all groups. All γ_i estimates are significantly larger than one. Further, $\gamma_3 - \gamma_2^2$ is significantly larger than zero, whereas $(\gamma_4 - \gamma_2^3) \cdot (\gamma_2 - 1) - (\gamma_3 - \gamma_2)^2$ does not differ significantly from zero, for each subgroup. Using results in Shohat and Tamarkin (1970), this implies that, for each subgroup, $G(v)$ can be approximated well by a discrete distribution with two positive points of support.

From the previous paragraph it follows that the moment-inequality specification tests proposed in subsection IID give mutually consistent results for each of the four subgroups in the data. In particular, neither of the three inequalities is rejected, for any subgroup, using conventional levels of significance. This supports our model specification. The fact that the γ_2 estimates significantly exceed one means that the data confirm that observed duration dependence (when going from $t = 0$ to $t = 1$) is more negative in the top of the cycle than in a recession. Blanchard and Diamond's (1994) so-called ranking model of unemployment predicts the opposite result. Apparently, in these data, the dynamic selection due to unobserved heterogeneity is empirically more important than ranking phenomena. In the next subsection, we will examine the implications of the γ_i estimates for the exit probabilities more closely.

From table 1 it also follows that there are seasonal effects in the heterogeneity distribution. The average success of individuals who become unemployed in a given month increases substantially from when this month is October to when it is March, to decrease again from March to October. This may be because in the fall a large proportion of the inflow into unemployment consists of school-leavers who did not find a job in anticipation of leaving school. These individuals have no work experience and may all compete for only a fraction of the set of jobs available.

It turns out that the specification test based on adding a calendar-time dependent term to the right-hand sides of the model equations confirms the model specification. We used the estimated model to perform residual analyses. The error variances are relatively large for black males and females. This probably reflects the fact that the average size of these groups in the data is relatively small, so that there may be considerable sample variation in the exit probability data. The SUNR contemporaneous error correlations are negative and generally close to zero. There is some evidence for positive first-order autocorrelation in the errors for a given equation.

So far, we have assumed that the success of the workers who are entering into unemployment is calendar-time independent except for seasonal fluctuations. We investigated the validity of this by estimating our model over two subperiods: 1967.04–1979.12 and 1980.01–1991.12. Appendix table A1 reports the duration dependence and heterogeneity estimates for these two subperiods. (In the estimation we allowed for seasonal effects, which are not presented.) The estimates are similar to those in table 1, indicating that the results are quite robust. We also estimated the model obtained by adding specification errors to the original equations (9) (rather than adding them after taking logs of the left- and right-hand sides). Again, the results are similar to those in table 1. The main difference is that for all groups the duration dependence is slightly less negative than in table 1.

We finish the discussion of our results by comparing them to the results on duration dependence and unobserved heterogeneity in the literature on parametric empirical analysis of unemployment durations within the MPH framework. Butler and McDonald (1986) estimate these phenomena in a parametric setting using CPS data. They take a Weibull specification for $\psi_1(t)$ and assume that $G(v)$ is a generalized gamma distribution, and they find evidence for the presence of unobserved heterogeneity and positive duration dependence (so $\psi_1(t)$ is increasing). However, their model does not account for dependence of the unemployment duration hazard on individual characteristics x or calendar time τ. Consequently, the model is nonparametrically unidentified, and the results on duration dependence and unobserved heterogeneity are determined by the assumed parametric functional forms for $G(v)$ and $\psi_1(t)$.

A number of studies based on U.S. unemployment duration data for male individuals estimate duration dependence and unobserved heterogeneity in a parametric setting, allowing for dependence of the hazard on observed explanatory variables x. The results in Flinn and Heckman (1983) are not statistically significant. Heckman and Singer (1984) find evidence for the presence of unobserved heterogeneity. They take a Weibull specification for $\psi_1(t)$ and find that the results on the sign of the duration dependence are very sensitive to the assumed family of distributions for $G(v)$.

Meyer (1990) uses a flexible functional form for $\psi_1(t)$ and assumes $G(v)$ belongs to the gamma family. He finds evidence for unobserved heterogeneity. Further, in general $\psi_1(t)$ does not display strong duration dependence during the first 3 months of unemployment. The hazard does display spikes near durations at which benefits entitlement ends, but these durations are well beyond the 4-month period we examine in our analysis. Thus, Meyer's (1990) results are not inconsistent with ours.

B. Implications

Using the information from table 1 we can study the evolution of the exit probability over the duration of unemployment for the different groups of workers in case of a stationary labor market ($\psi_2(\tau) \equiv \psi_2$ which is constant). In that case the evolution of the observed exit probability depends only on the heterogeneity distribution $G(v)$, the genuine duration dependence $\psi_1(t)$, and the state of the labor market (ψ_2) as indicated by the level of the observed exit probability for the first monthly duration class. To account for differences among the four groups in the third determinant we used the exit probability for the first month averaged over the period 1967–91. For white males this was 0.52, for white females 0.58, for black males 0.43, and for black females 0.52.

Figure *2a* shows how unobserved heterogeneity influences the average observed exit probabilities. Duration dependence is assumed to be absent. There is a strong relative decline of the exit probabilities, which is largest for black females and smallest for white males. Due to heterogeneity, the average observed exit probability in the fourth month is 54% of the exit probability in the first month for black females and 67% for white male workers. Figure *2b* shows the influence of genuine duration dependence, by assuming there is no unobserved heterogeneity. These results have been discussed above.

Figure *2c* shows the combined effect of duration dependence and heterogeneity. For white workers, duration dependence and heterogeneity work in the same direction on the observed exit probability. As a result, there is a substantial decline of the exit probability over the duration of unemployment. For white males, duration dependence is the dominant factor, whereas for white females unobserved heterogeneity dominates.

For black workers, duration dependence and heterogeneity generally work in opposite directions. However, the latter effect always dominates. As a result, figure 2*c* shows a substantially smaller decline for black individuals. After 2–3 months of unemployment the difference between white and black individuals has vanished. After 4 months, white individuals are worse off than black individuals. However, at that stage about 90% of all white individuals have already left unemployment.

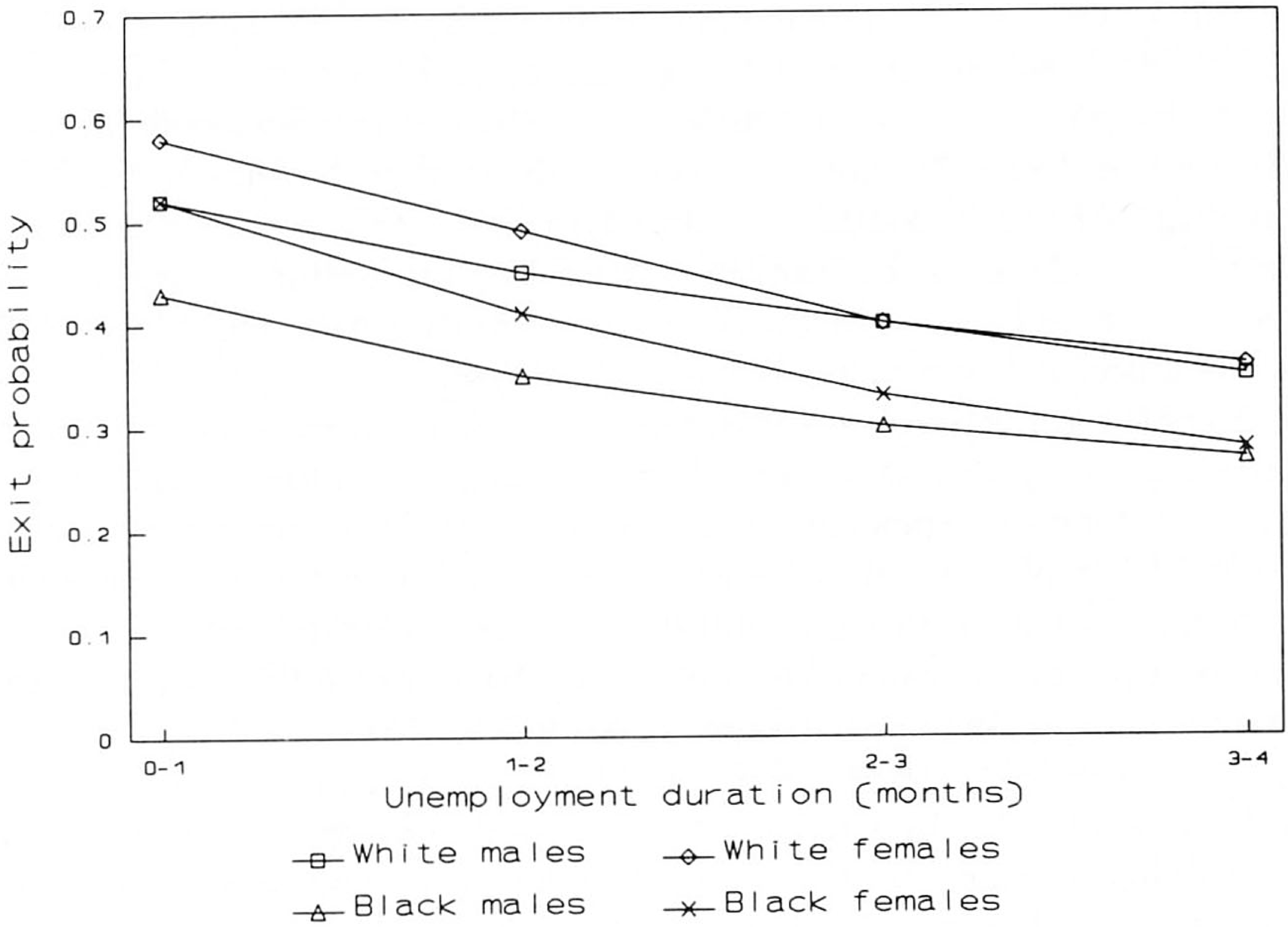
As noted in the previous subsection, the dynamic selection due to unobserved heterogeneity causes the observed exit probabilities to display less negative duration dependence in a recession than at the top of the business cycle. This implies that the relative importance of unobserved heterogeneity as a determinant of exit probabilities fluctuates over the cycle. Consider for example black males, who as a group have the largest var(v). In the average situation depicted in figure 2*a* ($\psi_2 = 0.43$, no duration dependence), the exit probability decreases from 0.43 at $t = 0$ to 0.27 at $t = 3$, which is a decrease of 36%. In a recession (typical value for ψ_2 of 0.38), the exit probability decreases from 0.38 to 0.26, which is a decrease of 33%. At the top of the cycle ($\psi_2 = 0.48$), the exit probability decreases from 0.48 to 0.29, which is a decrease of 39%. Clearly, the values of the exit probabilities at large t are relatively insensitive to the state of the business cycle. These results carry over to the situations that take account of duration dependence (cf. fig. 2*c*). Also, similar results hold for the other three groups.

As a consequence, in recessions, unobserved heterogeneity is less important as a determinant of observed exit probabilities. Also, to the extent to which there is a negative long-term trend in $\psi_2(\tau)$ over the data period (see fig. 1), unobserved heterogeneity is a less important determinant of exit probabilities in the early 1990s than it is in the late 1960s. This is particularly true for the groups with the largest heterogeneity, that is, black males and females. Note however from the previous paragraph that, quantitatively, the differences over the cycle are not large.

V. Conclusion

In this article, we show both theoretically and empirically that it is possible to distinguish unobserved heterogeneity from genuine duration dependence in unemployment durations by using aggregate time series on exit probabilities out of unemployment.

We analyze U.S. unemployment data for the period 1967–91 distinguishing four groups of workers: white males, white females, black males, black females. We find that unobserved heterogeneity is relevant for all four groups, causing the observed exit probability out of unemployment to decline over the duration of unemployment. Furthermore, we find diverging duration dependence effects between black and white workers. For white male individuals, the genuine duration dependence is most neg-



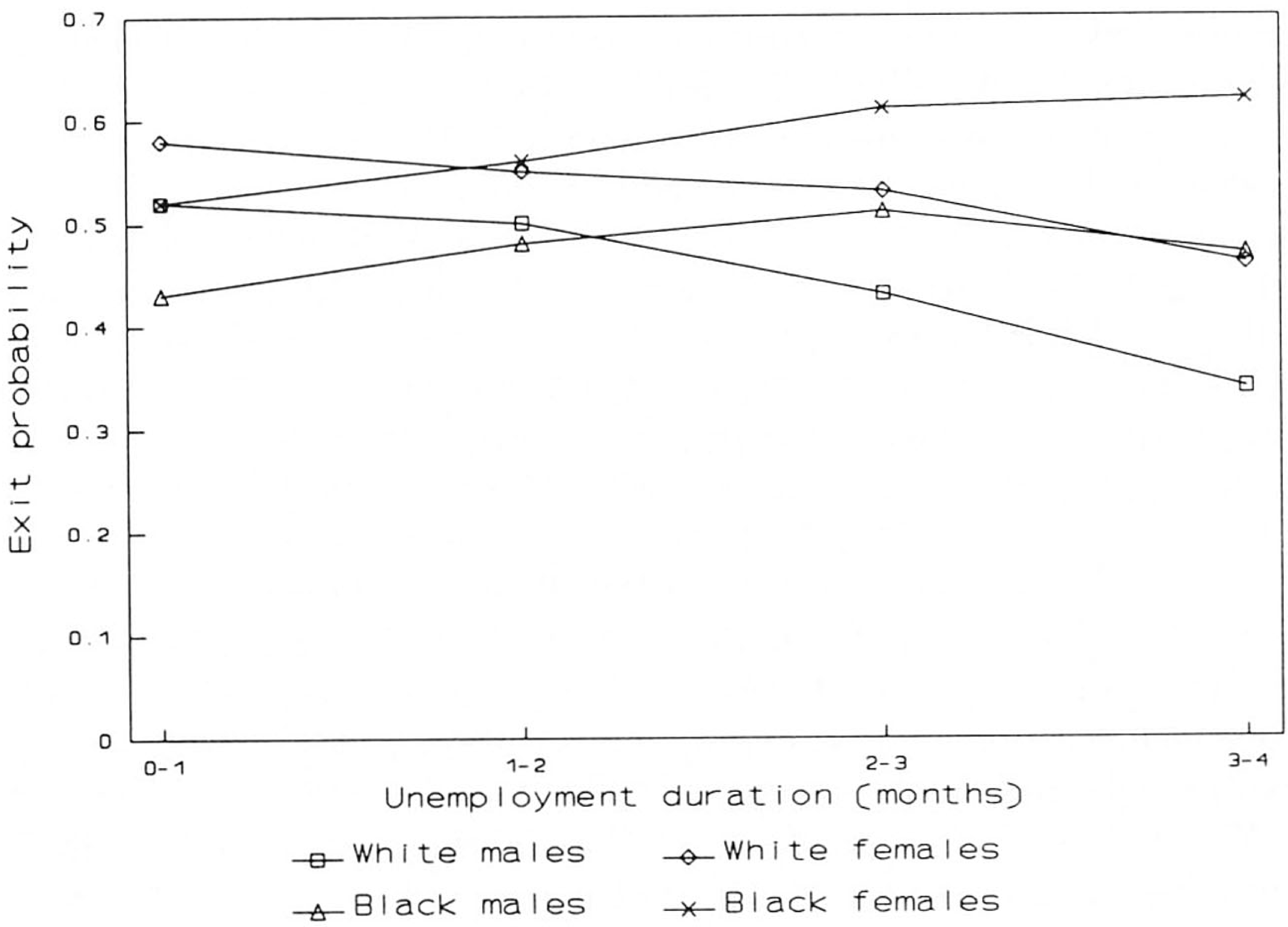


FIG. 2.—Exit probability out of unemployment over the duration of unemployment, in a stationary labor market. *a*, Unobserved heterogeneity; *b*, duration dependence; *c*, combined effect.

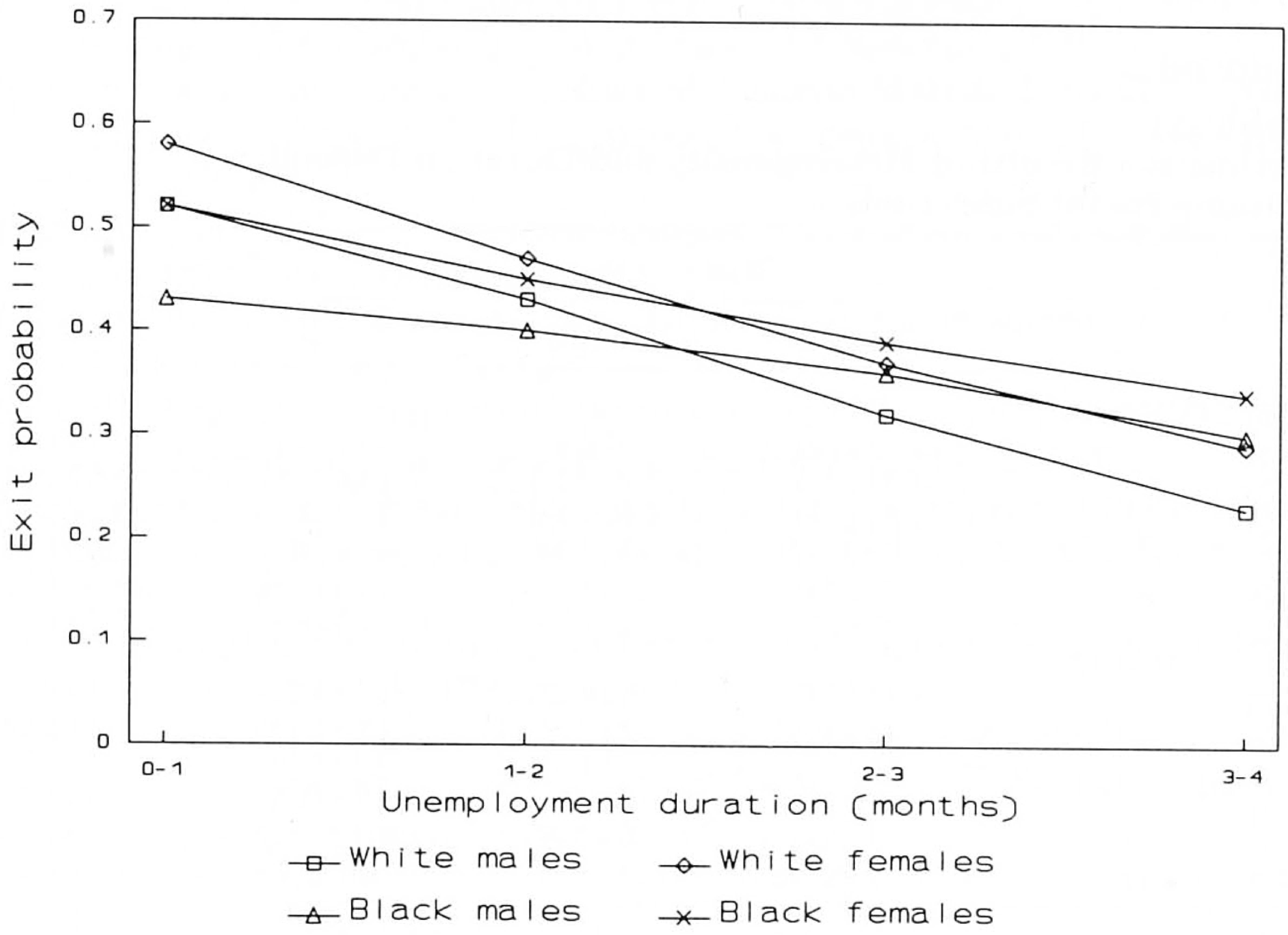


FIG. 2.—(*Continued*)

ative. The effect for white female individuals is smaller, but significant. For black individuals, we do not find significant negative duration dependence. From this we conclude that, in the U.S. labor market, duration dependent stigma effects related to unemployment durations are dominant for white workers, but not for black workers. Except for white males, though, the effect of unobserved heterogeneity dominates the duration dependence effect. Finally, there is a significant effect of the season at the moment of inflow into unemployment on the exit probability out of unemployment.

Several topics for future research emerge. First, it seems worthwhile to combine the aggregate data with micro data containing information on explanatory variables x. This might make it possible to estimate the quantities of interest under weaker assumptions.

Another topic for further research would be to improve the foundation of the stochastic specification of the equations of the empirical model. It is plausible that the aggregate observations on numbers of unemployed per duration class contain measurement errors (in particular for the groups of male and female blacks and for high-duration classes). However, it can be shown that incorporating this would lead to a model (i) with a complicated error covariance structure and (ii) that cannot be estimated with the method of this article. Consequently, it seems that any analysis based on such a model would have to be parametric.

Appendix

Table A1
Estimation Results of Heterogeneity and Duration Dependence Parameters for Subperiods

	White		Black	
	Male	Female	Male	Female
1967.04–1979.12:				
γ_2	1.12 (.02)	1.09 (.02)	1.21 (.02)	1.18 (.02)
γ_3	1.39 (.06)	1.27 (.07)	1.66 (.08)	1.51 (.07)
γ_4	1.86 (.14)	1.52 (.18)	2.43 (.20)	2.04 (.19)
η_1	.95 (.03)	.90 (.04)	1.06 (.06)	1.03 (.05)
η_2	.78 (.04)	.85 (.04)	1.08 (.08)	1.01 (.08)
η_3	.91 (.05)	.90 (.06)	.98 (.07)	1.13 (.11)
1980.01–1991.12:				
γ_2	1.14 (.04)	1.10 (.03)	1.24 (.04)	1.19 (.03)
γ_3	1.42 (.16)	1.23 (.13)	1.69 (.17)	1.53 (.12)
γ_4	1.95 (.45)	1.34 (.36)	2.33 (.50)	1.95 (.34)
η_1	.97 (.05)	.95 (.04)	1.15 (.06)	1.13 (.05)
η_2	.93 (.04)	1.05 (.04)	1.12 (.07)	1.18 (.07)
η_3	.79 (.04)	.91 (.06)	.97 (.08)	.89 (.08)

NOTE.—Standard errors are in parentheses.

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